Methodological considerations for analyzing ambulatory service access in multilevel context

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Abstract

As ambulatory surgery centers experience rapid development in recent years, service access has been identified as an important outcome measure that demands methodological considerations to support multilevel analyses. In this study, a literature review was conducted to illustrate existence of contextual factors, such as Proposition 10 funding for young children and tax incentives in high-need communities, which directly impacts the local capacity building. Variance of the service access has been partitioned at both county and community levels to reconfirm the need for multilevel studies. In comparison to randomized clinical trials in medical research, multilevel analyses can add contextual information to enhance examination of the hierarchical data structure in which communities are naturally nested within counties.

Keywords: Ambulatory Service Access, Multilevel Modeling, OSHPD Data Analysis.

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Introduction

Ambulatory surgery has been a rapidly growing sector of medical service for the past four decades [1]. Statistical methods are needed to support multilevel data analyses in different contexts to assess the service impact. Although randomized controlled trials (RCTs) have been held as the gold standard in medical research [2,3], Sandhu [4] observed that RCTs are under-represented in the surgical literature. In part, this is because ambulatory services are typically delivered under strict time constraints and are more intolerant of the uncertainty from random trials [5] .

In addition, "most RCT reports do not systematically discuss results within the context of similar research" [6] but, contextual factors are often needed to support result interpretation. Since "surgical trials often evaluated medical therapies in surgical patients as opposed to head-to-head comparisons of surgical technique" [4], patient origin inevitably contributes to the uncertainty of service outcomes [7]. The purpose of this investigation is to incorporate the perspective of multilevel modeling in examining the context of ambulatory service access beyond a simple RCT design.

Multilevel modeling is a relative new method. Bingenheimer and Raudenbush have stated, "Overzealous early adopters tout the method as a panacea, whereas critics charge that it offers nothing new to the field" [8]. In this article, the methodological need is addressed through literature reviews and empirical data analyses. As the world entered the Big Data era, many unknown confounders have been identified and incorporated in clinical trials [9]. The rapid increase of computing power also enhanced feasibility to apply multilevel modeling in statistical analyses. As a result, Sloane [10] suggested that "We change the basic research question from what works to what works for whom and in what contexts". Although it is beyond the capacity of a single article to completely describe the incorporation of confounding variables at numerous levels, this study is designed to introduce the statistical methodology toward better understanding of the empirical context for multilevel analyses.

Literature Review

Researchers believe that the RCT is effective in identifying what works [2]. Built on the causal inference from RCT, "The presumption is that once we had certain evidence of the outcomes of a set of practices we could then replicate that model of practice in many other places" [11]. The RCT implementation is also credited for transforming medical research from medieval charlatanry to a modern science [2,12]. In the past, "When the results of randomized trials conflict with results derived from other kinds of research, the former generally are seen as more authoritative and persuasive"[13].

Nevertheless, Cronbach [14] cautioned that randomization may be achieved at the expense of relevance. While randomization was effective in neutralizing contextual baselines [12], the needs for ambulatory service often arise accidentally, and cannot be arranged through a predetermined mechanism of randomization. For instance, the first ambulatory surgical procedure in the United States was conducted on a young girl who fell and suffered a penetrating head injury in 1650 [15]. In recent years, research has shown that 90 percent of a child's brain develops in the first five years of life, and that during the developing stage, infants and toddlers are more vulnerable to injuries. Thus, medical recovery demands more family attention after ambulatory surgery. Tourigny, Ward, and Lepage[16] reported that over the past few years, focus has increasingly turned towards the adjustment of parents whose child faces ambulatory surgery.

Although children do not vote on public policies, most parents do. In 1998, voters passed the California Children and Families Act, also known as Proposition 10, to designate child health as a focus area for the state commission[17]. The state revenue has been collected from a $.50 per pack tax on cigarettes or similar tobacco products to fund programs that support children aged 0-5 and their families. To ensure equity of the state investment, Proposition 10 funding is distributed according to the proportion of live births in each county[18] . Therefore, the policy impact has been trickled down from the state to counties, and cannot be subjected to randomization under RCT arrangements.

In comparison to other medical facilities, the freestanding ASC [Ambulatory Surgery Center] environment is less stressful since patients do not feel like they are being admitted to the hospital. This is especially beneficial to the pediatric patient population[19]. Young children typically lack experiences in self-protection, and their fragile body structures are more likely to be hurt inadvertently. Hence, ASC service access plays an important role in child health support. With rapid development of medical technology, many surgeries are switched from in-hospital environments to ASC facilities to curtail healthcare cost [20].

Despite their growth throughout the country (there are 5,500 to 6,000 ASCs in operation), a substantial number of ASCs still fail [21]. In particular, the challenge hinges on recruitment of surgeons who are committed to ASC services [22]. Consequently, several states offered income tax credits to attract medical professionals to underserved regions (Weldon, 2008). Cascardo [21] further cautioned that "a great staff is crucial to an efficient and profitable ASC". Since the capacity building varies across the local settings, community factors should be examined to assess the policy impact beyond a simple randomized trial [23].

In summary, ASC access is concurrently influenced by multilevel variables. While RCTs are effective in balancing the impact of confounders, the literature review has justified the need for examining contextual factors that cannot be subjected to randomization. Multilevel modeling offers an opportunity to incorporate profound factors of *population demand* and *service supply* in examining ASC access. In California, the population demand is supported by Proposition 10 funding at the county level for age-specific children. The service supply aspect is demonstrated by incentives for staff recruitment in ASC capacity building. If the contextual factors were treated as confounders in RCT, it could have made the research findings irrelevant to the local settings. Accordingly, incorporation of contextual factors is supported by the current literature for examining ASC access under a multilevel context.

Research Questions

Metzner and Kent [24] estimated that ambulatory surgical procedures comprise approximately 60% of all surgical procedures. Although large-scale data analyses seem pertinent to an examination of the widespread service delivery, the need for multilevel modeling eventually hinges on variability of the service access across county and community levels. In general, no contextual factors are needed unless the outcome variability has been identified at a particular level. Munnich [25] observed that "Until recently, standardized data on ambulatory surgery centers was difficult to access". To fill this void, two research questions are addressed in this investigation:

1. Is there a quality database to support multilevel analyses on ASC access?
2. What information can be employed to guide inclusion of contextual factors at different levels?

Both questions are grounded on practical needs in public health. Weber [26] noted that relative to hospitals, much less is known about ASCs, and few trustworthy national statistics are available. Thus, data identification in Question 1 provides an indispensable foundation for statistical analyses. Question 2 is designed to guide partition of the outcome variability for multilevel investigation.

Method

Data Selection

Healthcare costs have increased by 343% in California in less than two decades [27]. To monitor the trend of healthcare provision, the Office of Statewide Health Planning and Development (OSHPD) has been collecting ASC service data in California since 2005. In support of the multilevel data analyses, ambulatory facilities are required by California Health and Safety Code (Divison 107, Section 128737) to report patient locations across the entire state.

In the OSHPD data setting, communities are identified by zip code domains following the convention of U.S. Census Bureau [28]. The patient origin data naturally inherit a hierarchical structure in which communities are nested within counties. Although dissemination of the OSHPD data is grounded on the state statute, the OSHPD effort is still relatively new, and few researchers have employed the information to examine ambulatory surgery services in multilevel contexts. In this investigation, the OSHPD data are adopted to support analyses of ASC access in multilevel contexts.

Data Analysis

Sullivan, Dukes, and Losina [29] noted that medical research applications often involve hierarchical data structures. .The first step in estimating a multilevel model is to fit what is referred to as the null model [30]. that contains only intercept and corresponding error terms and is used to decompose the total variance [31].

From this perspective, Garson [32] described the null model as a baseline for multilevel analyses:

The *null model*, also called the "unconditional model" or a "one-way ANOVA with random effects," is a type of random intercept model that predicts the level 1 intercept of the dependent variable as a random effect of the level 2 grouping variable, with no other predictors at level 1 or 2 in a two-level model.

For a study of ASC service access, the outcome measure (Y_{ij}) at Level 1 is expressed as the sum of an intercept for county j and a random error (ε_{ij}) associated with the ith community in the jth county:

$$\text{Level 1: } Y_{ij} = \beta 0_j + \varepsilon_{ij} \tag{1}$$

where $\varepsilon_{ij} \sim N(0, \sigma^2)$

At level 2, the intercept (β_{0j}) for county j is modeled as the sum of an overall mean (γ_{00}) and a random deviation from the mean (u_{0j})

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + u_{0j} \tag{2}$$

where $u_{0j} \sim N(0, \tau_{00})$

As Gustafsson reported [33], "because there are now separate error terms for levels 1 and 2 (ε and u), it is possible to partition the variance across the two levels". In particular, Restricted Maximum Likelihood Estimation (REML) has an unbiased feature and can be employed for variance partition [34,35]. Bingenheimer and Raudenbush [8] concurred that for many types of data and a wide range of research questions, multilevel models provide a stronger basis for statistical inference than traditional, single-level models.

In summary, variance partition is conducted in this study to guide multilevel analyses of ambulatory service access at both community and county levels. The empirical data are gathered by OSHPD with support from the state statute to ensure information accuracy. In addition, the OSHPD data contain sufficient observations to assess multilevel variability. Introduction of contextual factors hinges on the existence of substantial variability in the measurement outcome. In this regard, adequate data collection is essential to "provide an accurate representation of the sources of variability [8].

Results

Descriptive Statistics

Delimited by the OSHPD data in California, this study covers a total of 1,746 communities that have valid zip code identifications from the U.S. Census Bureau[36]. Due to the time for data processing, the 2012 OSHPD data have been released in 2014. At the community level, the annual ASC access ranges from zero to 108, resulting in an average 27.84 accesses per community and a standard deviation (SD) of 24.92.

When the results are aggregated to the county level, the annual count of ASC access varies from 73 to 19,968 across 50 counties. On average, the ASC access per county is 1,436.63 with SD equal to 2,969.72. Since various communities are clustered by counties, the average findings show more ASC access and larger SD values at the county level (Table 1).

Table 1 Descriptive Statistics for ASC Access Count across Counties and Communities.

Unit of Analysis	Mean	SD
County	1436.63	2969.72
Community	27.84	24.92

Jia et al [37] further suggested variance partitioning at different levels to reflect the fact that communities from the same county might be more similar than their counterparts across different counties. Unlike the results in Table 1, results in Table 2 are based on concurrent estimation of the variability components ($\sigma 2$ and τ_{00}) in equations (1) and (2). At the county level, fitting this simple model provides an estimate of τ_{00}, as well as a test of the null hypothesis that $\tau_{00} = 0$[8]. When the OSHPD data are subject to the multilevel analysis, the results reconfirm significant variations of ASC service access at county level ($Z=4.07$, $p<.0001$), which support rejection of the null hypothesis, H_0: $\tau_{00} = 0$. Similarly, the multilevel analysis shows significant variability of ambulatory service access (σ^2) at the community level ($Z=35.27$, $p<.0001$). Hence, the results support multilevel analyses of contextual factors to explain the outcome variability at both community and county levels.

Table 2 Covariance Parameter Estimates.

Level	Variance	Standard Error	Z	p
County	67.97	16.71	4.07	<.0001
Community	526.79	14.94	35.27	<.0001

Discussion

This study illustrated an alternative method to avoid treating multilevel attributes as confounders in randomized controlled trials. According to Hedges and Rhodes[38], the randomized experiment is the only method known that can yield model-free unbiased estimates of causal effects. Alternatively, other methods inevitably incorporate additional model assumptions. A major assumption of multilevel model is that estimates of the treatment effect are distributed normally around their true value[39]. Since the OSHPD data contain a sufficient number of observations at each level, the central limit theorem guarantees that the model assumption is approximately true.

Information in Tables 1 and 2 also provides an opportunity to compare the result differences between a single-level model and a multilevel model. Apparently, variability of ASC access depends on the size of measurement unit at a particular level. In general, each county includes multiple communities. Thus, small communities may have no ASC access in the results. Similarly, the size variation also occurs at the county level. While Alpine County has around 1,000 residents, Los Angeles County houses a population of over 10 million people. Therefore, ASC access further depends on geographic locations.

Approximately 17% of Californians live in a MUA Medically Underserved Areas (MUA)[40]. The 2012 OSHPD data also indicated no report of ambulatory service access in eight out of 58 counties, which counts 14% of the units at the county level. Multilevel analyses provide additional opportunities to examine the service access gap at both county and community levels.

Without considering the multilevel structure, excessive Type I errors could be produced from examining contextual factors at Level 1[8]. Such analyses ignore the fact that data within the same county tend to be more correlated than the data from different counties, causing the precision of the parameter estimate to be overstated. For instance, if standard errors were computed from the SD values in Table 1, the result could have been 0.60 at the community level, much smaller than the corresponding multilevel analysis result of 14.94 in Table 2.

Before the advent of specialized software for multilevel data analyses, an alternative approach was to average the lower-level data within a cluster and use the result as an outcome in a single level analysis across clusters[41]. However, an embedded assumption is to disregard variability of the research outcome at the lower level. That assumption does not fit for a study of ASC access because of the coexistence of significant variability at both county and community levels (Table 2). In the past, Bingenheimer and Raudenbush[8] linked the unit choice to statistical power analysis, and asserted that "compared with the single-level analysis of (adjusted) cluster-specific means, multilevel models offer advantages of convenience and flexibility. In most cases they also provide greater statistical power".

Another way to reconfirm the need for multilevel modeling is through an examination of intraclass correlation (ICC). Roberts (2004) noted that "if intraclass correlation exists, then the traditional linear model must be abandoned because the assumption of independent observations has been violated" (p.32). Symbol ($\widehat{\rho}$) is used to represent the estimated ICC (Raudenbush & Bryk, 2002). Based on the results in Table 2, we have

$$\widehat{\rho} = \frac{\hat{\tau}_{00}}{\hat{\tau}_{00} + \hat{\sigma}^2} = \frac{67.97}{67.97 + 526.79} = .11$$

The results show that ($\widehat{\rho}$) value is not negligible. Hence, in comparison to traditional linear models, multilevel modeling is not built on the assumption of independent observations in RCT, and can provide a better fit to the empirical data from OSHPD.

The incorporation of zip codes for community identification also facilitates the information merge between OSHPD and other databases, such American Community Survey from the US Census Bureau, to expand the contextual factor examinations in future studies. Mark Twain was quoted to comment, "History doesn't repeat itself, at best it sometimes rhymes". Built on the ongoing collection of OSHPD data, trends of ambulatory service access can be examined on the time dimension. Erickson[42] cautioned, "The future continues to be original, the local refuses to hold still. General prescriptions for practice do not fit the circumstances of specific situations". Accordingly, more multilevel analyses should be conducted to make research findings more relevant to specific situations.

In summary, two research questions have been addressed in this study. For the first question, OSHPD data have been identified to articulate multilevel analyses of ASC access under a hierarchical context in which communities are clustered within counties. Although randomization balances both known and unknown confounders in RCTs to support result replications[2], ASC access often depends on heterogeneity of service populations that are subject to influences of state and federal policies, such as Proposition 10 funding and tax incentives in MUAs. Instead of suggesting abandonment of RCT, methodological discussion is incorporated in examining the second research question to supplement RCT with other forms of evidence, such as consideration of the policy impact across counties and communities, to triangulate the result of ASC access under multilevel contexts.

References

1. Sapp D. (2011). Factors influencing the decision makers of hospitals to adopt strategic alliances with physicians in ambulatory surgery centers. Minneapolis, MN: Capella University (UMI Number: 3460524).
2. Cartwright N, Munro E. The limitations of randomized controlled trials in predicting effectiveness. ***Journal of Evaluation in Clinical Practice*** 2010;**16**:260–6.
3. Mohan V. Clinical trial phases. ***International Journal of Clinical Medicine*** 2014;**5**:1374-83.
4. Sandhu L. (2013). An empirical study of bias in randomized controlled trials and non-randomized studies of surgical interventions. Toronto: University of Toronto. Retrieved from https://tspace.library.utoronto.ca/bitstream/1807/65452/3/Sandhu_Lakhbir_201311_PhD_thesis.pdf.
5. Platt R. (2010). Distributed data networks. In L. Olsen & J. McGinnis (Eds.), R***edesigning the clinical effectiveness research*** (pp. 254-265). Washington, DC: National Academies Press.
6. Wijeysundera D, Austin P, Hux J, Beattiec W, Laupacis A. Bayesian statistical inference enhances the interpretation of contemporary randomized controlled trials. ***Journal of Clinical Epidemiology*** 2009;**62**:13e21.
7. Meakins JL. Innovation in surgery: The rules of evidence. A***merican Journal of Surgery*** 2002;**183**:399-405.
8. Bingenheimer J, Raudenbush S. Statistical and substantive inferences in public health: Issues in the application of multilevel models. ***Annual Review of Public Health*** 2004;**25:**53–77.
9. Wang S. (2013). Opportunities and challenges of clinical research in the big-data era: from RCT to BCT. ***Journal of Thoracic Disease*** 2013;**5**:721-3.
10. Sloane F. Through the looking glass: Experiments, quasi-experiments, and the medical model. ***Educational Researcher*** 2008;**37(1)**:41-6.
11. Erickson F. Scaling down: A modest proposal for practice-based policy research in teaching. ***Education Policy Analysis Archives*** 2014; **22**:2-7.
12. Clay, R. (2010). More than one way to measure. Retrieved from http://www.apa.org/monitor/2010/09/trials.aspx
13. Riehl C. Feeling better: A comparison of medical research and education research. ***Educational Researcher*** 2006;**35(5)**:24-9.
14. Cronbach LJ. (1982). ***Designing evaluations of educational and social problems***. San Francisco: Jossey-Bass.
15. Earle AS. (Ed.). (1983). ***Surgery in America: From the colonial era to the twentieth century***. New York, NY: CBS.
16. Tourigny J, Ward V, Lepage T. Fathers' behavior during their child's ambulatory surgery. ***Issues in Comprehensive Pediatric Nursing*** 2004;**27**:69–81.
17. Wang J, Henderson J, Harniman J. An empirical study of coexisting relationships between area-specific support and early childhood development. ***Journal of Social Service Research*** 2013;***39(2)***:141-58.
18. Snider D. (2013). An investment in children. Retrieved from http://www.redbluffdailynews.com/business/ci_24465756/denise-snider-an-investment-children.
19. Charoo E. (2011). ***Critical success factors of medicare-certified ambulatory surgery centers: A qualitative collective case study***. Minneapolis, MN: Capella University (UMI Number: 3481001).
20. Sapp D. (2011). ***Factors influencing the decision makers of hospitals to adopt strategic alliances with physicians in ambulatory surgery centers***. Minneapolis, MN: Capella University (UMI Number: 3460524).
21. Cascardo D. (2014). Guidelines for setting up an ambulatory surgery center. ***Podiatry Management*** 2014; **33(8)**;127-32.
22. Fischer B, Dugel P, Vazeen M. Insights into ambulatory surgery centers. ***Ophthalmology Times*** 2007;**32**(Supplement):2-8.
23. McGee R, Gaventa J. (2010). ***Review of impact and effectiveness of transparency and accountability initiatives***. London: Institute of Development Studies
24. Metzner J, Kent C. Ambulatory surgery: Is the liability risk lower? ***Current Opinion in Anaesthesiology***, 2012;**25(6)**:654-8.
25. Munnich E. (2013). ***Essays in health economics***. Notre Dame, IN: University of Notre Dame (UMI Number: 3585305).
26. Weber E. (2009). ***Measuring welfare from ambulatory surgery centers: A spatial analysis of demand for healthcare facilities***. Chicago, IL: University of Chicago (UMI Microform 3369506).
27. Consumer Attorneys of California (2015). Medical malpractice fibs and facts. Retrieved from https://www.caoc.org/index.cfm?pg=MICRAFibs.
28. California Department of Finance (2013). 2012 American Community Survey (1-year estimates): Health insurance coverage. Sacramento, CA: Author.
29. Sullivan L, Dukes K, Losina E. Tutorial in biostatistics: An introduction to hierarchical linear modeling. ***Statistics in Medicine*** 1999;**18**:855-88.
30. O'Connell A, Reed S. (2012). Hierarchical data structures, institutional research, and multilevel modeling. In J. Lott & J. Antony (Eds.), ***New directions for institutional research***. San Francisco: Jossey-Bass.
31. Hox J. (2014). Introduction multilevel analysis. Retrieved from http://www.ccsr.ac.uk/qmss/summer/Leuven11/documents/Lecture3_Multilevel.pdf.
32. Garson GD. (2013). Fundamentals of hierarchical linear and multilevel modeling. In GD Garson (Ed.), ***Hierarchical Linear Model: Guide and application***. Thousand Oaks, CA: Sage.
33. Gustafsson M. Using the hierarchical linear model to understand school production in South Africa. ***South African Journal of Economics*** 2007;**75**:84-98.
34. Cressie N, Lahiri S. (1993). The asymptotic distribution of REML estimators. ***Journal of Multivariate Analysis*** 1993;**45**:217-33.
35. Viechtbauer W. Bias and efficiency of meta-analytic variance estimators in the random-effects model. J***ournal of Educational and Behavioral Statistics***, 2005;**30**:261-93.
36. Zipcodestogo (2011). California ZIP code list. Retrieved from http://www.zipcodestogo.com/California/
37. Jia H, Moriarty D, Kanarek N. (2009). County-level social environment determinants of health-related quality of life among US adults: A multilevel analysis. ***Journal of Community Health*** 2009;**34**:430-9.
38. Hedges L, Rhodes C. (2014). ***Quasi-experimental designs: Can we estimate causal relations without randomization?*** Paper presented at the Institute on Education Research Methods for Faculty from Minority Serving Institutions, Evanston, IL.
39. Raudenbush SW, Bryk AS. (2002). ***Hierarchical Linear Models: Applications and data analysis methods*** (2nd ed.). Thousand Oaks, CA: Sage Publications.
40. State of California (2010). Medically Underserved Area (MUA) designation: Find underserved areas in California. Retrieved from http://gis.oshpd.ca.gov/atlas/topics/shortage/mua.
41. O'Connell A, Reed S. (2012). Hierarchical data structures, institutional research, and multilevel modeling. In J. Lott & J. Antony (Eds.), ***New directions for institutional research***. San Francisco: Jossey-Bass.
42. Erickson F. Scaling down: A modest proposal for practice-based policy research in teaching. ***Education Policy Analysis Archives*** 2014; **22**:2-7.